CALIBRATING ACTIVITY-BASED MODELS WITH EXTERNAL OD INFORMATION: AN OVERVIEW OF DIFFERENT POSSIBILITIES

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ABSTRACT

Many practitioners question the advantages of activity-based models over conventional four-step models in terms of replication of traffic counts. Therefore, in this paper, a framework is highlighted that actively links travel demand models in general, and activity-based models in particular, with traffic counts. Two approaches are presented that calibrate activity-based models with traffic counts, namely an indirect and a direct approach. The indirect approach tries to incorporate findings, based on the analysis of traffic counts, into the model components of the activity-based models. The direct approach calibrates the parameters of the travel demand model in such a way that the model replicates the observed traffic counts (quasi-)perfectly. A practical example is provided to illustrate the direct approach. The study area for this practical example is Hasselt, a Belgian city of about 70,000 residents, and its surrounding municipalities**.** The practical examples revealed that there is not a single roadway to success in calibrating activity-based models, but that different options exist in fine-tuning the activity-based model. Notwithstanding, it is important to recognize some open issues and avenues for further research. First, it is not always appropriate to assume that traffic counts are completely correct. Setting up some belief-structure might increase the responsiveness of the activity-based model. In addition, the OD-matrix calibration that optimizes the correspondence between estimated and observed screen-line counts could negatively impact the correspondence to other measures such as vehicle miles traveled. To conclude, formulation of a multi-objective calibration method is a key challenge for further research.

1 BACKGROUND

Due to an increased environmental awareness, current travel demand models pursue higher levels of behavioral realism. Four periods can be distinguished in this evolution of travel demand modeling approaches. The first period, the late 1950's, is typified by a steep increase in car use. During this period, trip-based models were developed to make long term projections of travel demand in order to assess major investments in road infrastructure. These first generation models assumed that travel is the result from four consecutive steps, namely trip generation, trip distribution, mode choice and route choice (*1*). From the mid 1970's until the 1990's, the focus shifted towards the travel needs of a single person. The original four-step models were replaced by theories about utility maximizing behavior and individual choice behavior. Discrete choice models such as multinomial logit models and more advanced statistical techniques formed the core of so-called tour-based systems (*2*). From the mid 1990's and early 2000's activity-based travel demand models became a rising modeling paradigm. The basic premise of these third generation models is the fact that travel behavior is a derivative from the activities that an individual performs (*1*). Current dynamic activity-based models, such as Aurora and Feathers (*3*), taking into account different forms of learning could be seen as a fourth generation of travel demand models.

Although modern activity-based travel demand models have clear theoretical advantages over conventional four-step models – the most important ones are the fact that all basic travel decisions can be applied in a disaggregate fashion, the explicit linkages between the travel decisions of members of a single household, the consistent choices for a single person across all travel decisions and the disaggregate way of handling the time-of-day of travel decisions – conventional models still dominate the travel demand modeling paradigm (*4,5*). Davidson *et al.* (*6*) highlighted several reasons that explain the acceptance of and resistance to more sophisticated model frameworks. They can be broadly categorized as the degree of resistance to new modeling technology and the size of encouragement forces. The reasons include the size of the public agency, the size of the jurisdiction, the level of institutional history and the level of state support for travel demand forecasting. Davidson *et al.* (*6*) also stressed that in order to reinforce the transition from conventional models towards activity-based models, it is imperative that the objective theoretical advantages of activity-based models are better explained to practitioners and communicated more actively.

This paper focuses on a concern that stems from misunderstanding and mistrust by practitioners. Although researchers have acknowledged the advantages of an exhibited behavioral realism to policy analysis, many practitioners question the advantages of activity-based models over conventional four-step models in terms of replication of traffic counts, as it is in many respects easier to adjust a conventional travel demand model to fit base level traffic counts exactly than an activity-based micro-simulation model (*6*). In this regard, it is important to stress the distinction between static model accuracy in terms of the replication of the base-year observed data, and the responsive properties of the model that are related to the quality of the travel forecasts for future and changed conditions, as these two model properties do not necessarily coincide. Therefore, in this paper, different techniques are highlighted that actively link activity-based models in particular, and travel demand models in general, with traffic counts in order to achieve the desired responsive properties – the model being sensitive to demographic changes and policy measures – of the travel demand models as well as the replication of traffic counts. Note that proper calibration is a crucial step in simulation models as findings based on inappropriately calibrated models could be misleading and even erroneous (*7*). An overview of new calibration and validation standards, as well as best practice examples for travel demand modeling, is provided by Schiffer and Rossi (*8*). Bear in mind that the calibration of an activity-based model is not unlike calibrating a conventional four-step model (*5*). A thorough example of the calibration of a conventional four-step model with traffic counts is provided by Cascetta and Russo (*9*). For an excellent example concerning the calibration of an activity-based travel demand model (i.e. the Sacramento activity-based travel demand model) the reader is referred to Bowman et al. (*10*).

The remainder of the text is organized as follows. Section 2 provides an outline of the suggested techniques that are implemented in a practical example, which are thoroughly discussed in Section 3. Finally, some general conclusions and avenues for further research are indicated.

2 LINKAGES BETWEEN ACTIVITY-BASED MODELS AND TRAFFIC COUNTS

There are two possible approaches to link activity-based models in particular, and travel demand models in general, with traffic counts, namely an indirect and a direct approach. The first approach tries to incorporate findings, based on the analysis of traffic counts, into the model components of the activity-based models. The second approach calibrates the model parameters of the activity-based model in such way that the model replicates the observed traffic counts (quasi-)perfectly (less than 5% error on average). The following subsections will elaborate and further clarify the two methods of linking activity-based models with traffic counts.

2.1 Indirect Linkage

The ‘indirect linkage’-approach tries to identify events that affect travel behavior and resulting traffic patterns. Analysis of traffic counts for instance can be used to identify effects of holidays and weather events (*11*). These traffic swaying events can then be used to alter the impedance functions used in route choice modules. When events such as holidays and weather conditions are identified, their impact on travel behavior can even be further elucidated by analyzing activity diary data. Utility functions that express the propensity of performing certain activities – note that basically the utility functions of all elements of the activity-pattern generation can be modified in this way – can then explicitly incorporate explanatory variables to account for the events that were analyzed. In this regard, activity-diary collection tools that integrate geographical information logging, such as the PARROTS-tool (*12*), provide the required data to perform detailed analysis, for instance on route choice. It can be expected that the explicit incorporation of events that account for the variability in revealed traffic patterns and their underlying reasons, will result in both an improved responsiveness of the activity-based model and a better replication of traffic counts.

2.2 Direct Linkage

The ‘direct linkage’-approach tries to fine-tune the model parameters of the activity-based (AB) model in such a way that the model-based traffic counts correspond maximally to the observed ones on the network. Calibration opportunities exist at four levels (Figure 1): the data level, the model level, the OD-matrix level and the assignment level.

Two approaches can be followed when considering calibration at the data level: a ‘crude’ approach, where data (personal/household information, zonal information) is altered in order to achieve a better correspondence to the benchmark measures, and a ‘fine’ approach where agents (individuals or households) are weighted. The first approach immediately raises questions concerning the validity and the credibility: adjusting fields or adding or deleting records undermines the validity of the model and should be avoided. The latter approach attributes weights to the different agents. For the practical example discussed in Section 3, the weights are chosen to be natural numbers (including zero) such that these weights correspond to exact counterparts in the real population. Fractional weights like 0.8 or 1.2 would also have been feasible, but the interpretation of these weights would be a probability of this agent to have an exact counterpart in the real population (0.8 would correspond to a change of 80% of having an exact counterpart in the real population, and 1.2 would be interpreted as 80% chance of having one counterpart in the real population, 20% of having two counterparts in the real population). The use of weights can be justified by the fact that there exist groups of individuals with similar travel behavior that can be captured in representative activity patterns (RAPs). By using these RAPs, the complete activity-generation can be performed in a hands-on manner (*13*). McNally (*14*) and Wang (*15*) have even further advocated the use of RAP’s by showing that RAP’s are relatively stable over conventional planning horizons (up to 10 years). Weighting agents thus seems to be a worthwhile path to follow. Notwithstanding, the weighting procedure can become computationally very intensive as the number of possible weights increases with the number of simulated agents.

A second calibration possibility arises at the model level. The activity schedule generation could be altered in such a way that the obtained OD-matrix optimally reproduces the observed traffic counts. One solution to achieve this optimal state is an ‘updating’-process which alters the scheduling rules that are derived from the available travel survey data. In addition, zone-specific rules can be introduced: for instance increasing the probability of certain destination choices, or increasing the probability of performing a certain activity. In that way, the production and attraction of these zones can be fine-tuned. When different forecasting scenarios are desired, it is necessary to keep the updated rules that were defined by the updating-process in the baseline year. In that manner the AB-model is constructed in a consistent way. Hence, linking activity-based models with traffic counts by making behavioral adjustments (altering rules) might prove to be a valid way of overcoming practitioners’ mistrust.

The OD-matrix level is the third level at which calibration opportunities arise. The OD-matrix is obtained by the simultaneous activity schedule execution of all agents. This OD-matrix can then be benchmarked in function of the screen-line counts. Different techniques exist to estimate OD-matrices from traffic counts. In practice, most models assume or require that a target OD-matrix is available. This target OD-matrix (the OD-matrix resulting from the activity-based model) is a crucial part of prior information. In statistical approaches, the target OD-matrix is typically assumed to stem from a sample survey and is regarded as an observation of the “true” OD-matrix. The observed set of traffic count data may also be assumed to be an observation of the “true” traffic count data, and therefore (small) deviations between estimated counts and observed counts may be accepted. Thus, the purpose of the calibration process is to find an OD-matrix which produces “small” differences between the estimated link flows and the observed flows. Three modeling philosophies are postulated in the transportation literature (*16*): traffic modeling based approaches, statistical inference approaches and gradient based solution techniques.

The traffic assignment module is the last level where calibration is possible. Obviously the way of attributing origin-destination flows to the network plays a crucial role in how well the model-based traffic counts correspond to the benchmark measures. Ortúzar and Willumsen (*17*) classify traffic assignment methods according to their treatment of congestion (inclusion of capacity restraints) and their treatment of differences in objectives and perceptions by agents (inclusion of stochastic effects).

3 PRACTICAL EXAMPLE

In this section, a numerical example is provided to further illuminate the 'direct linkage'-approach. The study area for this numerical example is Hasselt, a Belgian city of about 70,000 residents, and its surrounding municipalities. Activity-travel information derived from census data, from the Flemish travel survey and from the origin-destination (OD) matrix assigned in the multimodal travel demand model Flanders, is combined to generate a simulated "true" population and its corresponding travel behavior. The data from this true population is assumed to be unbiased and precise. For generating the "true" representative activity patterns (RAPs) at population level, people are supposed to perform activities in a predefined order: first, people perform a work or school activity, then they go shopping, afterwards they perform a leisure trip, and finally, they perform other type of activities. In addition to this predefined order, it is presumed that people perform a specific type of activity at most once (the exact chances to perform a specific activity are given in the upper part of Table 1). Furthermore, it is assumed that residents return home after their last activity.

To focus on the general ideas behind the different calibration techniques presented, and to reduce model complexity, route choice modeling (traffic assignment) and mode choice modeling were not taken into account. Thus, the practical example focuses on the first three levels of calibration. Assuming perfect knowledge about these aspects procures the property that the quality of the output of the (activity-based) travel demand model is completely related to the aggregated OD-matrix resulting from the individual activity patterns. In addition, owing to the perfect knowledge of these aspects, traffic counts on the different roads form an identity match to the origin-destination flows. Note that the assumption of perfect knowledge about origin-destination relationships nowadays become a more viable option. When privacy issues are explicitly addressed, data from a mobile phone network can be used to derive origin-destination patterns (*18*). Results from Caceres *et al.* (*19*) and González *et al.* (*20*) indicate that extracting OD-information from mobile phone records has great potential and is much more cost-efficient that those generated with traditional techniques.

As complete information about all activity-patterns seldom is available, the starting point for the calibration exercises is a 2.5% stratified random sample of the "true" population (municipality is taken as the stratification variable). The lower part of Table 1 provides more information about the 2.5% sample: the number of residents in each municipality, as well as the municipality specific propensities to perform different activities, are displayed.

Table 2 presents the OD-matrix obtained from aggregating the individual activity persons from all people in the population (upper part of the Table 2) and the sample (lower part of the Table 2). The OD-information from the sample is scaled up to the population level for comparison purposes. A side-note has to be made concerning the "true" population origin-destination matrix. When the origin-destination flows of this matrix are compared to flows really observed in practice, the population OD-matrix overestimates the flows observed in practice.

This is due to the fact that all residents from the municipalities in this practical example are assumed to perform their activities within the entire study area.

The absolute percentage difference (APE) between the true population and the sample is displayed in the lower part of Table 2. Many of these APEs are larger than 5% indicating that some extra calibration is needed to improve the correspondence with the "true" observed values. The absolute percentage is defined as:

$$APE = \begin{cases} \dfrac{abs\left(T_{ij}^{pop} - T_{ij}^{sa}\right)}{T_{ij}^{pop}} & if \ T_{ij}^{pop} > 0 \\ 0 & if \ T_{ij}^{pop} = T_{ij}^{sa} = 0 \\ infinity\ value & if \ T_{ij}^{pop} = 0, T_{ij}^{sa} > 0 \end{cases}$$

where T_{ij} represents the number of trips from municipality *i* to municipality *j, pop* indicates that the flow corresponds to the population, and *sa* that the flow corresponds to the sample. A possible infinity value could be one, indicating that you are of the target by 100%. Such an infinity value has to be defined, as many calculations are infeasible when values are divided by zero (and thus mathematically are equal to infinity). Since the "true" population OD-matrix contains no zero cells, no infinity value had to be defined in the practical example.

3.1 Calibration at the Data Level

The goal of weighting agents is to procure the highest possible resemblance between the observed traffic counts on the network and the predicted traffic counts by the activity-based model. In the non-calibrated model all agents are equally weighted (weights equal to the inverse of the sample size). By iteratively altering the weights, an optimal correspondence can be found using meta-heuristics (a meta-heuristic is a general algorithmic framework that can be used to guide heuristic methods to search for feasible solutions to different optimization problems). Two different approaches can be distinguished when agents have to be weighted. The first approach weights the agents before their activity pattern is generated. Since agents are duplicated before the activity patterns are generated, the activity patterns of the replicated agents - created by the weights – can differ from the ones of the "true" agents. Thus, the convergence of the iterative process of weighting persons and calculating the activity patterns of the "agents" and their replicates is not necessarily guaranteed. The second approach solves this convergence problem by weighting the activity patterns instead of the agents themselves. Take for example a resident in Hasselt, who only performs a work activity in Diepenbeek. From Table 2 one can see that if this persons weight would be decreased, both the estimated OD-flows from Hasselt to Diepenbeek and Diepenbeek to Hasselt would be reduced, and thus be closer to the "true" OD-flows for the population.

To illustrate the calibration of OD-matrices at the data levels, the second approach, the weighting of activity patterns, is followed. The RAPs of the residents in the sample are weighted using the algorithm displayed in Figure 2. Note that the algorithm that is implemented includes an element originating from tabu search meta-heuristics, namely the concept of a tabu list. A tabu list is a short-term memory where, in this case, the persons whose weights have been altered, are stored (*21*). The tabu list ensures that these weights are not altered multiple times within the same iteration, thus preventing situations like for instance the repetitive increasing and decreasing of the weight of a specific person. Two versions of the algorithm were implemented. The first one changed the weights by adding or subtracting one. The second one altered the weights by increasing or reducing the weights by a random number between one and ten, reducing the risk of converging towards the same saddle point (i.e. the same (sub)-optimum). A safeguard was included, procuring non-negative weights.

The estimated OD-matrices are provided in Table 3. The mean absolute percentage error (MAPE) of the estimated matrix using the first algorithm equals 2.12%, whereas the second matrix has a MAPE of 2.02%. From Table 4 one could notice that for two cells in both matrices the APE is higher than 0.5. This is due to the fact that the very few people are traveling between these two locations (Kortessem and Nieuwerkerken), and in line with this, that the persons in the sample travelling between these locations, also travel between other uncommon OD-pairs (Kortessem – Herk-De-Stad and Kortessem – Lummen). This underlines the importance of including a stop criterion in the algorithms to avoid an endless computation.

3.2 Calibration at the Model Level

The basic model that will be calibrated, first predicts activity chains for all persons (the proportions of the different activity chains have been fixed to the population proportions), and then predicts the locations where the different activities will be performed. Note that the proportions of the different activity chains have been fixed to the population proportions. This ensures that discrepancies between the “true population” OD-matrix, and the calibrated OD-matrix are only due to differences in destination choices (location probabilities). Thus, at the model-level, the activity schedule generation could be altered by iteratively updating the probabilities of certain destination choices (related to their respective activity purposes). The adjustment of the model parameters is straightforward in this case as only one dimension is considered at a time (i.e. the location probabilities). After all, the other parameters (such as the chances of performing certain activities) are kept constant. For real activity-based models in practice, a chain of interlinked choices with feedbacks are modeled, and thus multiple parameters have to be changed simultaneously. This would seriously augment the complexity of the model, but the basic framework elucidated in this paper, still could be used.

The updating process will attain a quasi-perfect match when the updated sample probabilities of the destination choices are equal to the unknown population probabilities. Nonetheless, a full search of the solution space (investigating all possible combinations of location probabilities for the different activities) is not a feasible option, as the number of possible combinations approaches infinity. The number of possible combinations can be computed as follows:

$$1/\ \text{1-precision of location probability}^{\text{number of activities} \times \text{number of municipalities}^2},$$

which for the practical example discussed in this paper (applying a precision of 1%) would yield a total number of possible combinations of 10^{500} (approximating infinity). Therefore, an algorithm that explores the solution space for a ‘good’ solution instead of the optimal solution should be implemented.

In order to calibrate the activity-based travel demand model, and to ensure convergence of optimization algorithms, it is essential that the variability caused by the activity-generation process is reduced as much as possible. Stability of the activity-generation can be ensured by taking averages over multiple (activity-generation) runs, so that differences between the estimated OD-matrix and the true population OD-matrix are not the result of random variations, but of the altered location probabilities. However, guaranteeing the stability of the activity generation diminishes the performances, as computation times are significantly increased. The algorithm that is used is shown in Figure 3.

Table 5 presents the OD-matrix and corresponding APEs for the model-based calibration results. From these results, one could see that here is a decrease in the mean absolute percentage error from 20,27% in the up-scaled sample OD-matrix to 6,29% in the model-calibrated OD-matrix (after 100 iterations). Nevertheless, as multiple activity-generations are required in each step of the algorithm, model-based calibration is the most computer-intensive calibration option, favoring other calibration techniques.

3.3 Calibration at the Matrix Level

The third level of calibration tackled in this study is the matrix level. Recall that perfect knowledge about route choice and mode choice is assumed, and that an identity match is presumed between traffic counts and origin-destination flows. Therefore the calibration at the matrix level, like the two previous calibration levels discussed, is illustrated using OD-pair information. The reader is referred to Abrahamsson (*16*) for a thorough literature review concerning the calibration of OD-matrices using traffic counts. Three situations are explored in order to calibrate the survey OD-matrix.

3.3.1 Perfect Knowledge about Inter-Zonal Traffic

In the first situation, it is assumed that “perfect” knowledge is available about all inter-zonal traffic flows, but that information about intra-zonal traffic is only available at survey level. Let $P_i = \sum_j T_{ij}$ be the number of trips originating from municipality *i* (production), $A_j = \sum_i T_{ij}$ the number of trips arriving in municipality *j* (attraction), and T_{ij} the number of trips from zone *i* to zone *j*. Then the intra-zonal traffic flows ($T_{ij,i=j}$) could be approached by the following formula:

$$T_{ij,i=j} = \lambda \left(P_i^{est} - P_i^{*,pop} \right) + \left(1 - \lambda \right) \left(A_j^{est} - A_j^{*,pop} \right),$$

where $\lambda \in \left[0,1 \right]$ expresses the relative importance that is given to the number of trips originating in a municipality, compared to the number of trips arriving in a municipality, where *est* indicates that the quantity is derived from the estimated (survey) OD-matrix, and *pop* indicates that the quantity is derived from the population “true” OD-matrix. The asterisk underlines that the fact that the intra-zonal traffic flows are not included in the population row ($P_i^{*,pop} = \sum_{j,j \neq i} T_{ij}^{pop}$) and column totals ($A_j^{*,pop} = \sum_{i,i \neq j} T_{ij}^{pop}$). As it is often assumed that production is estimated more accurately than attraction (*17*), in this practical example three times more confidence is placed in the estimation of productions than in the estimation of attractions. Thus, the intra-zonal origin-destination flows are calculated as follows:

$$T_{ij,i=j} = 0.75 \left(P_i^{est} - P_i^{*,pop} \right) + 0.25 \left(A_j^{est} - A_j^{*,pop} \right).$$

The resulting OD-matrix is given in the upper part of Table 6. Note that when it is assumed that the activity-travel pattern of people begin and end in the home location (like it is the case for the practical applications described in this paper), the number of trips originating from a municipality equals the number of trips arriving in that municipality. In this case the choice of λ is irrelevant. From Table 7 it is clear that only the intra-zonal trips are altered (APEs for inter-zonal trips equal zero).

3.3.2 Growth Factor Modeling (Furness Iteration)

The second situation considers the case in which two OD-matrices (one on population level and one derived from the sample) are available. Information from these OD-matrices can be combined using growth factor modeling. One option is to take the cell information from the population (e.g. retrieved from GPS tracks) and the trip totals (column and row totals of the OD-matrix) from the survey. A second option is the reverse, namely taking the cell information from the survey, and the trip totals from the population. To illustrate the technique, the first option is implemented. This option is the more realistic one, as in practice precise OD-pair information can be derived using cell phone information at fairly low costs, while surveys capture well the total travel demand. The doubly constrained growth factor model is estimated using Furness iterations. Formally, the number of trips from municipality *i* to *j* (T_{ij}) is calculated as follows:

$$T_{ij} = t_{ij} \times a_i \times b_j ,$$

where t_{ij} is the number of trips (in the population OD-matrix), and where a_i and b_j are balancing factors. These balancing factors are a set of correction coefficients which are appropriately applied to the cell entries in each row or column. The iterative procedure starts with setting all b_j equal to one. In the second step, the a_i are solved for b_j to satisfy the trip production constraint (row totals of the cell entries of the population OD matrix have to equal the productions derived from the survey). Subsequently, in the third step, the b_j are solved for the a_i, calculated in the previous step, to satisfy the trip attraction constraint (column totals of the cell entries of the population OD matrix have to equal the attractions derived from the survey). Then, the OD matrix is updated. This consecutive calculation of a_i and b_j is repeated until convergence is achieved (both the production and attraction constraints are satisfied). The procedure yields the matrix presented in the middle of Table 6, the corresponding APEs in Table 7.

3.3.3 "Perceived Precision" Updating

The third and final situation that is explored to illustrate potential calibration options at the data level, describes the case in which an outdated population-based OD-matrix, as well as a recent matrix derived from the sample are available. The procedure is an adaptation of the Bayesian updating procedure discussed by Atherton and Ben-Akiva (*22*). This procedure updates information using the following formulae:

$$\vartheta_{updated} = \frac{\dfrac{\vartheta_{prior}}{\sigma^2_{prior}} + \dfrac{\vartheta_{updating}}{\sigma^2_{updating}}}{\dfrac{1}{\sigma^2_{prior}} + \dfrac{1}{\sigma^2_{updating}}} \text{ and } \sigma^2_{updated} = \frac{1}{\dfrac{1}{\sigma^2_{prior}} + \dfrac{1}{\sigma^2_{updating}}},$$

where ϑ is the mean of the investigated quantity and σ^2 the variance of the mean of that quantity. As the OD-cells in an OD-matrix are fixed numbers, of which the variance is seldom reported, one could replace the mean of the quantity by the OD-flow and reformulate the formulae in terms of perceived precision (ψ) instead of variance of the mean (since the precision increases as the variance decreases). This perceived precision can for instance be obtained via expert knowledge. The formulae then take the form of the following equations:

$$T_{ij}^{new} = \frac{\dfrac{T_{ij}^{pop}}{1-\psi^{pop}} + \dfrac{T_{ij}^{sa}}{1-\psi^{sa}}}{\dfrac{1}{1-\psi^{pop}} + \dfrac{1}{1-\psi^{sa}}} \text{ and } \psi^{new} = 1 - \frac{1}{\dfrac{1}{1-\psi^{pop}} + \dfrac{1}{1-\psi^{sa}}}.$$

For the practical example discussed in this paper the perceived precision of the population OD-matrix is set equal to 99% and the one of the sample OD-matrix equal to 95%. Note that the updated OD-matrix then has a precision of 99,17%. The updated OD-matrix is shown in the lower part of Table 6. For reasons of completeness and comparability with other calibration techniques, the APEs for this method are also presented (Table 7), even though interpretation of these specific APEs is meaningless, as the premise of this example was outdated population data.

3.4 Discussion of Proposed Techniques

An interesting issue of calibration to traffic counts is the fact that traffic counts themselves are uncertain. Uncertainty can be tackled in the data-level and model-level based calibration by adjusting the converge criterion, i.e. absolute percentage errors (denoted as fitness values by Park and Qi (*7*)). When choosing between the different techniques suggested in this paper, three key issues have to be taken into account: computational complexity, data availability and sensitivity to policy issues.

The most computer-intensive method was the model-based calibration, requiring 14 days of computation on a computer with a Core 2 Duo 2.10 GHz CPU and 4GB RAM. This large computation time was due to the fact that the calibration at this level involves running the full simulation model (*23*, *24*). In comparison, the iterative procedure for calibration at the data-level took about 1 day, and the matrix-level techniques only required a few seconds of computation (the latter techniques did not include iterative optimization techniques). Note that the computation times of the iterative procedures could be decreased by using more efficient optimization algorithms, such as genetic algorithms (*7*) and golden section search (*25*).

Next to the computational complexity, the available target data will definitely will influence the suitability of the different techniques. The largest amount of target data is required for the model-based calibration, since for each subpart of the model, target information is necessary.

Finally, the influence of the calibration techniques on the sensitivity of the model to policy measures is of high importance. This sensitivity depends on how the base year calibration manipulations (i.e. calibrations weights) are transferred towards future predictions. Further research on the policy sensitivity of the different approaches should be a key priority for further research.

4 CONCLUSIONS AND FURTHER RESEARCH

In this paper, different possibilities for linking travel demand models in general, and activity-based models in particular, with traffic counts and precise OD-matrix information are highlighted and illustrated by means of an example. The discussed techniques provide the framework to overcome one of the main concerns by practitioners, namely the disadvantage of activity-based models over conventional four-step models in terms of the replication of traffic counts. The practical examples revealed that there is not a single roadway to success in calibrating activity-based models, but that different options exist in fine-tuning the activity-based model. Therefore, a careful assessment of the available options is needed to determine which choices have to be made. A step-wise procedure, combining elements of the different proposed solutions, can be recommended.

Notwithstanding, it is important to recognize some open issues and avenues for further research. First, it is not always appropriate to assume that traffic counts are completely correct. In reality, differences may relate to sampling bias, variability in travel, imperfect counts, assumptions about non-passenger cars (e.g. freight traffic) and external traffic, and unreliability in model facets. Setting up some belief-structure might increase the responsiveness of the activity-based model. Secondly, the OD-matrix calibration that optimizes the correspondence between estimated and observed screen-line counts could negatively impact the correspondence to other measures such as vehicle miles traveled. Thus, formulation of a multi-objective calibration method is a key challenge. Third, in most cases in practice, travel demand models are validated and tested against hour-specific counts. The same methodology can be applied in this case: modeled trip tables must be compared to counts for each time-of-day period. The challenge herein, exists in consolidating the time-of-day specific adjustments into a set of activity-generation, location and schedule adjustments. Finally, further testing the calibration possibilities within a real activity-based travel demand modeling environment would further provide empirical evidence of the proposed frameworks. In particular, the investigation of how the policy sensitivity of an activity-based model is affected by the different approaches should be a key priority for further research.

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LIST OF TABLES AND FIGURES

TABLE 1 Number of Residents and Propensities of Activity Participation

		"True" population				
Municipality	**No. of residents**	**% Work**	**% School**	**% Shopping**	**% Leisure**	**% Other**
1: Hasselt	70 584	29.59%	14.22%	33.28%	27.94%	25.92%
2: Diepenbeek	17 874	34.30%	30.49%	30.47%	25.30%	23.47%
3: Kortessem	8 153	33.83%	16.39%	33.88%	19.66%	21.59%
4: Alken	11 090	27.92%	17.60%	37.76%	25.35%	24.82%
5: Nieuwerkerken	6 685	28.02%	17.71%	41.74%	22.03%	22.11%
6: Herk-De-Stad	11 874	32.52%	21.32%	35.20%	21.10%	23.61%
7: Lummen	13 874	31.38%	16.38%	37.03%	21.19%	21.77%
8: Heusden-Zolder	31 017	24.54%	17.95%	32.19%	24.18%	23.63%
9: Zonhoven	20 060	30.06%	17.57%	31.42%	24.32%	24.79%
10: Genk	64 095	25.35%	18.32%	28.77%	25.85%	23.79%
		Sample				
Municipality	**No. of residents**	**% Work**	**% School**	**% Shopping**	**% Leisure**	**% Other**
1: Hasselt	1 765	28.90%	13.88%	32.52%	30.71%	25.89%
2: Diepenbeek	447	35.35%	27.07%	30.43%	23.27%	23.94%
3: Kortessem	204	35.78%	14.22%	31.37%	25.98%	21.57%
4: Alken	277	29.96%	18.41%	36.82%	24.55%	23.83%
5: Nieuwerkerken	167	23.95%	20.36%	40.72%	23.35%	20.96%
6: Herk-De-Stad	297	32.32%	18.86%	36.03%	21.55%	22.56%
7: Lummen	347	28.82%	20.46%	35.73%	24.50%	20.46%
8: Heusden-Zolder	775	24.13%	16.52%	33.29%	25.81%	21.16%
9: Zonhoven	502	30.88%	22.71%	34.06%	26.89%	26.10%
10: Genk	1 602	27.47%	17.04%	28.34%	25.22%	23.78%

TABLE 2 OD-Matrices Retrieved from the "True" Population and the Sample

"True" population										
From\to	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	130 888	8 142	2 692	8 239	2 620	4 580	2 899	5 270	7 108	8 928
2	8 299	22 167	1 292	744	163	283	306	825	1 281	7 682
3	2 715	1 310	8 704	522	111	106	88	137	227	1 125
4	8 278	731	518	11 780	723	656	273	322	515	673
5	2 591	151	117	721	7 052	1 683	305	219	184	335
6	4 637	318	109	648	1 614	14 892	1 852	732	316	555
7	2 891	304	95	260	308	1 907	19 398	3 272	652	783
8	5 220	837	149	314	232	721	3 281	46 967	2 953	1 960
9	7 224	1 290	241	530	175	311	673	2 915	22 160	5 621
10	8 623	7 792	1 128	711	360	534	795	1 975	5 744	112 725
Sample										
From\to	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	132 800	8 440	3 120	7 600	2 440	4 960	3 120	5 440	7 440	8 240
2	8 520	21 680	800	840	160	440	320	1 160	1 160	7 160
3	3 040	880	9 480	640	40	200	120	280	320	1 160
4	7 920	840	600	11 240	600	600	240	200	400	640
5	2 560	160	40	680	7 000	1 520	240	280	320	280
6	4 800	440	200	600	1 600	14 280	1 720	600	240	680
7	3 200	360	160	240	320	1 760	19 560	2 720	480	1 160
8	5 240	1 160	240	120	240	600	2 880	46 200	3 760	2 000
9	7 560	1 200	400	640	320	240	520	3 400	23 400	6 040
10	7 960	7 080	1 120	680	360	560	1 240	2 160	6 200	112 920
Absolute Percentage Difference										
From\to	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	1.5%	3.7%	15.9%	7.8%	6.9%	8.3%	7.6%	3.2%	4.7%	7.7%
2	2.7%	2.2%	38.1%	12.9%	1.8%	55.5%	4.6%	40.6%	9.5%	6.8%
3	12.0%	32.8%	8.9%	22.6%	64.0%	88.7%	36.4%	104.4%	41.0%	3.1%
4	4.3%	14.9%	15.8%	4.6%	17.0%	8.5%	12.1%	37.9%	22.3%	4.9%
5	1.2%	6.0%	65.8%	5.7%	0.7%	9.7%	21.3%	27.9%	73.9%	16.4%
6	3.5%	38.4%	83.5%	7.4%	0.9%	4.1%	7.1%	18.0%	24.1%	22.5%
7	10.7%	18.4%	68.4%	7.7%	3.9%	7.7%	0.8%	16.9%	26.4%	48.2%
8	0.4%	38.6%	61.1%	61.8%	3.5%	16.8%	12.2%	1.6%	27.3%	2.0%
9	4.7%	7.0%	66.0%	20.8%	82.9%	22.8%	22.7%	16.6%	5.6%	7.5%
10	7.7%	9.1%	0.7%	4.4%	0.0%	4.9%	56.0%	9.4%	7.9%	0.2%

TABLE 3 OD-Matrices Calibrated Using Weighted RAPs

					Algorithm 1					
From\To	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	132 196	8 181	2 702	8 194	2 594	4 608	2 871	5 298	7 044	8 855
2	8 291	21 972	1 282	738	160	285	304	817	1 269	7 751
3	2 688	1 319	8 781	526	32	107	88	138	225	1 130
4	8 241	738	513	11 715	716	650	271	325	517	670
5	2 567	160	46	727	7 038	1 667	302	217	185	338
6	4 611	315	107	654	1 630	14 762	1 842	739	314	559
7	2 915	307	95	262	311	1 896	19 585	3 240	648	777
8	5 179	845	148	311	234	714	3 309	46 563	2 959	1 955
9	7 263	1 302	242	525	174	314	676	2 887	22 286	5 565
10	8 592	7 730	1 118	704	358	530	788	1 993	5 787	113 222
					Algorithm 2					
From\to	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	132 173	8 223	2 712	8 160	2 610	4 584	2 874	5 306	7 038	8 873
2	8 332	21 987	1 282	744	160	285	304	818	1 284	7 720
3	2 695	1 323	8 728	526	40	111	88	138	226	1 120
4	8 227	724	514	11 814	718	650	271	324	519	667
5	2 601	160	40	718	6 985	1 670	303	219	185	337
6	4 610	315	111	654	1 630	14 906	1 859	729	313	557
7	2 905	304	95	262	311	1 920	19 570	3 240	657	779
8	5 182	844	148	314	232	714	3 307	46 870	2 966	1 942
9	7 273	1 302	239	527	175	313	667	2 896	22 292	5 565
10	8 555	7 734	1 126	709	357	531	800	1 979	5 769	113 457

TABLE 4 Absolute Percentage Errors (Calibration Using Weighted RAPs)

					Algorithm 1					
From\to	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	1.00%	0.48%	0.37%	0.55%	0.99%	0.61%	0.97%	0.53%	0.90%	0.82%
2	0.10%	0.88%	0.77%	0.81%	1.84%	0.71%	0.65%	0.97%	0.94%	0.90%
3	0.99%	0.69%	0.88%	0.77%	71.17%	0.94%	0.00%	0.73%	0.88%	0.44%
4	0.45%	0.96%	0.97%	0.55%	0.97%	0.91%	0.73%	0.93%	0.39%	0.45%
5	0.93%	5.96%	60.68%	0.83%	0.20%	0.95%	0.98%	0.91%	0.54%	0.90%
6	0.56%	0.94%	1.83%	0.93%	0.99%	0.87%	0.54%	0.96%	0.63%	0.72%
7	0.83%	0.99%	0.00%	0.77%	0.97%	0.58%	0.96%	0.98%	0.61%	0.77%
8	0.79%	0.96%	0.67%	0.96%	0.86%	0.97%	0.85%	0.86%	0.20%	0.26%
9	0.54%	0.93%	0.41%	0.94%	0.57%	0.96%	0.45%	0.96%	0.57%	1.00%
10	0.36%	0.80%	0.89%	0.98%	0.56%	0.75%	0.88%	0.91%	0.75%	0.44%
					Algorithm 2					
From\to	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	0.98%	0.99%	0.74%	0.96%	0.38%	0.09%	0.86%	0.68%	0.98%	0.62%
2	0.40%	0.81%	0.77%	0.00%	1.84%	0.71%	0.65%	0.85%	0.23%	0.49%
3	0.74%	0.99%	0.28%	0.77%	63.96%	4.72%	0.00%	0.73%	0.44%	0.44%
4	0.62%	0.96%	0.77%	0.29%	0.69%	0.91%	0.73%	0.62%	0.78%	0.89%
5	0.39%	5.96%	65.81%	0.42%	0.95%	0.77%	0.66%	0.00%	0.54%	0.60%
6	0.58%	0.94%	1.83%	0.93%	0.99%	0.09%	0.38%	0.41%	0.95%	0.36%
7	0.48%	0.00%	0.00%	0.77%	0.97%	0.68%	0.89%	0.98%	0.77%	0.51%
8	0.73%	0.84%	0.67%	0.00%	0.00%	0.97%	0.79%	0.21%	0.44%	0.92%
9	0.68%	0.93%	0.83%	0.57%	0.00%	0.64%	0.89%	0.65%	0.60%	1.00%
10	0.79%	0.74%	0.18%	0.28%	0.83%	0.56%	0.63%	0.20%	0.44%	0.65%

TABLE 5 Model-Based Calibrated OD-Matrix and Corresponding APEs

Model-Based Calibrated OD-Matrix

From\to	1	2	3	4	5	6	7	8	9	10
1	131 667	8 088	2 822	8 140	2 553	4 634	2 970	5 391	7 071	8 617
2	8 307	21 901	1 153	783	178	319	331	909	1 211	7 554
3	2 830	1 188	8 814	554	98	126	107	183	258	1 174
4	8 159	759	543	11 487	690	623	234	265	544	711
5	2 506	172	101	689	7 063	1 665	303	236	220	355
6	4 692	341	124	628	1 591	14 879	1 815	682	324	615
7	2 972	333	107	228	312	1 843	19 266	3 149	635	857
8	5 306	918	190	263	235	685	3 188	46 990	3 064	2 044
9	7 154	1 241	269	545	224	321	631	3 014	21 894	5 772
10	8 359	7 706	1 208	699	367	597	856	2 063	5 844	112 689

Model-Based Calibrated APEs

From\to	1	2	3	4	5	6	7	8	9	10
1	0.60%	0.66%	4.84%	1.21%	2.54%	1.17%	2.44%	2.30%	0.52%	3.48%
2	0.10%	1.20%	10.78%	5.24%	9.20%	12.84%	8.28%	10.18%	5.44%	1.66%
3	4.24%	9.34%	1.27%	6.19%	11.41%	18.55%	21.97%	33.58%	13.51%	4.33%
4	1.43%	3.88%	4.83%	2.49%	4.56%	5.08%	14.29%	17.70%	5.63%	5.65%
5	3.27%	14.13%	13.68%	4.48%	0.16%	1.05%	0.77%	7.76%	19.38%	5.97%
6	1.19%	7.34%	14.07%	3.09%	1.45%	0.09%	2.00%	6.83%	2.64%	10.81%
7	2.79%	9.43%	12.28%	12.44%	1.19%	3.36%	0.68%	3.75%	2.66%	9.45%
8	1.65%	9.64%	27.74%	16.14%	1.15%	5.04%	2.84%	0.05%	3.76%	4.27%
9	0.96%	3.80%	11.62%	2.77%	27.81%	3.22%	6.29%	3.38%	1.20%	2.69%
10	3.06%	1.11%	7.12%	1.69%	1.85%	11.86%	7.67%	4.46%	1.74%	0.03%

TABLE 6 OD-Matrices Calibrated Using Matrix Level Possibilities

	Situation 1: Perfect Knowledge about Inter-Zonal Traffic									
From\To	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	133 122	8 142	2 692	8 239	2 620	4 580	2 899	5 270	7 108	8 928
2	8 299	21 365	1 292	744	163	283	306	825	1 281	7 682
3	2 715	1 310	9 819	522	111	106	88	137	227	1 125
4	8 278	731	518	10 591	723	656	273	322	515	673
5	2 591	151	117	721	6 774	1 683	305	219	184	335
6	4 637	318	109	648	1 614	14 379	1 852	732	316	555
7	2 891	304	95	260	308	1 907	19 488	3 272	652	783
8	5 220	837	149	314	232	721	3 281	46 773	2 953	1 960
9	7 224	1 290	241	530	175	311	673	2 915	24 740	5 621
10	8 623	7 792	1 128	711	360	534	795	1 975	5 744	112 618
	Situation 2: Growth Factor Modeling (Furness Iteration)									
From\To	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	132 854	8 085	2 839	8 008	2 606	4 556	2 925	5 294	7 449	8 984
2	8 241	21 536	1 333	707	159	275	302	811	1 313	7 563
3	2 863	1 352	9 535	527	115	110	92	143	247	1 176
4	8 046	695	523	10 964	688	625	264	310	517	648
5	2 577	147	121	687	6 871	1 640	302	216	189	330
6	4 611	309	113	617	1 573	14 513	1 831	720	325	548
7	2 919	301	100	251	305	1 886	19 468	3 268	679	783
8	5 243	822	155	302	228	710	3 278	46 688	3 062	1 952
9	7 569	1 322	262	532	180	319	702	3 023	23 972	5 839
10	8 677	7 671	1 179	685	355	526	796	1 967	5 967	112 457
	Situation 3: "Perceived Precision" Updating									
From\To	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	131 207	8 192	2 763	8 132	2 590	4 643	2 936	5 298	7 163	8 813
2	8 336	22 086	1 210	760	162	309	308	881	1 261	7 595
3	2 769	1 238	8 833	542	99	122	93	161	242	1 131
4	8 218	749	532	11 690	702	647	267	302	496	667
5	2 586	152	104	714	7 043	1 656	294	229	207	326
6	4 664	338	124	640	1 612	14 790	1 830	710	303	576
7	2 942	313	106	257	310	1 882	19 425	3 180	623	846
8	5 223	891	164	282	233	701	3 214	46 839	3 087	1 967
9	7 280	1 275	267	548	199	299	647	2 996	22 367	5 691
10	8 512	7 673	1 127	706	360	538	869	2 006	5 820	112 758

TABLE 7 Absolute Percentage Errors (Calibration Using Matrix Level Possibilities)

Situation 1: Perfect Knowledge about Inter-Zonal Traffic

From\To	1	2	3	4	5	6	7	8	9	10
1	1.71%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
2	0.00%	3.62%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
3	0.00%	0.00%	12.81%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
4	0.00%	0.00%	0.00%	10.09%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
5	0.00%	0.00%	0.00%	0.00%	3.94%	0.00%	0.00%	0.00%	0.00%	0.00%
6	0.00%	0.00%	0.00%	0.00%	0.00%	3.44%	0.00%	0.00%	0.00%	0.00%
7	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.46%	0.00%	0.00%	0.00%
8	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.41%	0.00%	0.00%
9	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	11.64%	0.00%
10	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.09%

Situation 2: Growth Factor Modeling (Furness Iteration)

From\To	1	2	3	4	5	6	7	8	9	10
1	1.50%	0.70%	5.46%	2.80%	0.53%	0.52%	0.90%	0.46%	4.80%	0.63%
2	0.70%	2.85%	3.17%	4.97%	2.45%	2.83%	1.31%	1.70%	2.50%	1.55%
3	5.45%	3.21%	9.55%	0.96%	3.60%	3.77%	4.55%	4.38%	8.81%	4.53%
4	2.80%	4.92%	0.97%	6.93%	4.84%	4.73%	3.30%	3.73%	0.39%	3.71%
5	0.54%	2.65%	3.42%	4.72%	2.57%	2.55%	0.98%	1.37%	2.72%	1.49%
6	0.56%	2.83%	3.67%	4.78%	2.54%	2.54%	1.13%	1.64%	2.85%	1.26%
7	0.97%	0.99%	5.26%	3.46%	0.97%	1.10%	0.36%	0.12%	4.14%	0.00%
8	0.44%	1.79%	4.03%	3.82%	1.72%	1.53%	0.09%	0.59%	3.69%	0.41%
9	4.78%	2.48%	8.71%	0.38%	2.86%	2.57%	4.31%	3.70%	8.18%	3.88%
10	0.63%	1.55%	4.52%	3.66%	1.39%	1.50%	0.13%	0.41%	3.88%	0.24%

Situation 3: "Perceived Precision" Updating

From\To	1	2	3	4	5	6	7	8	9	10
1	0.24%	0.61%	2.65%	1.29%	1.15%	1.38%	1.27%	0.54%	0.78%	1.28%
2	0.44%	0.37%	6.35%	2.15%	0.31%	9.25%	0.76%	6.77%	1.57%	1.13%
3	2.00%	5.47%	1.49%	3.77%	10.66%	14.78%	6.06%	17.40%	6.83%	0.52%
4	0.72%	2.49%	2.64%	0.76%	2.84%	1.42%	2.01%	6.31%	3.72%	0.82%
5	0.20%	0.99%	10.97%	0.95%	0.12%	1.61%	3.55%	4.64%	12.32%	2.74%
6	0.59%	6.39%	13.91%	1.23%	0.14%	0.68%	1.19%	3.01%	4.01%	3.75%
7	1.78%	3.07%	11.40%	1.28%	0.65%	1.28%	0.14%	2.81%	4.40%	8.02%
8	0.06%	6.43%	10.18%	10.30%	0.57%	2.80%	2.04%	0.27%	4.55%	0.34%
9	0.78%	1.16%	11.00%	3.46%	13.81%	3.80%	3.79%	2.77%	0.93%	1.24%
10	1.28%	1.52%	0.12%	0.73%	0.00%	0.81%	9.33%	1.56%	1.32%	0.03%

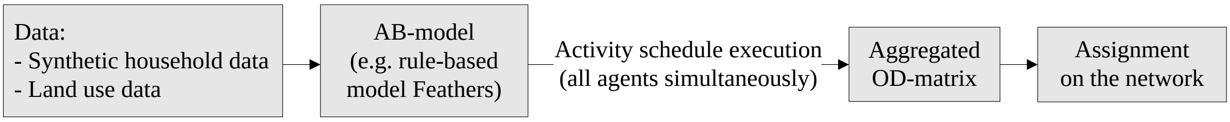

FIGURE 1 Four levels of calibration opportunities.

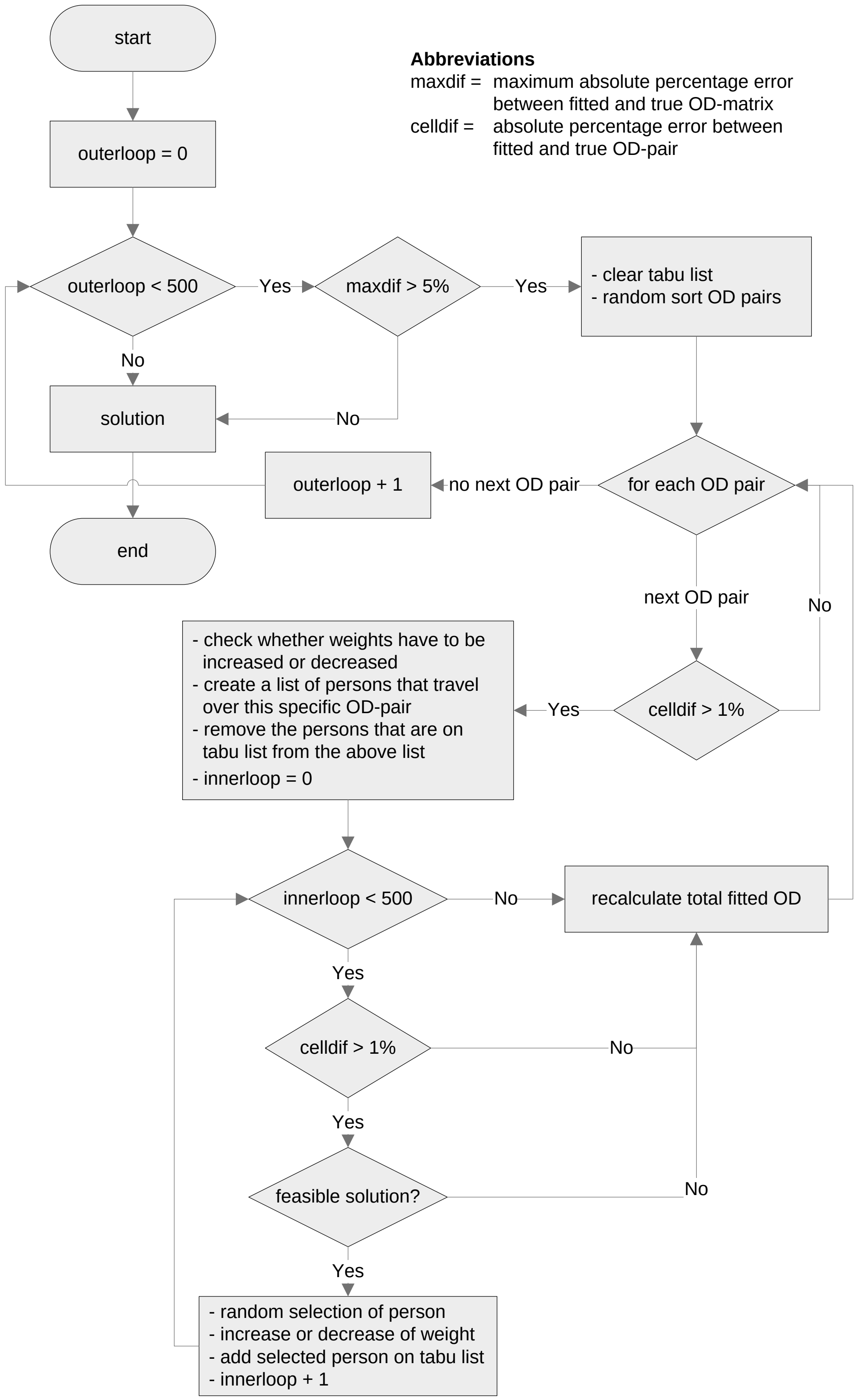

FIGURE 2 Calibration algorithm to weight representative activity patterns.

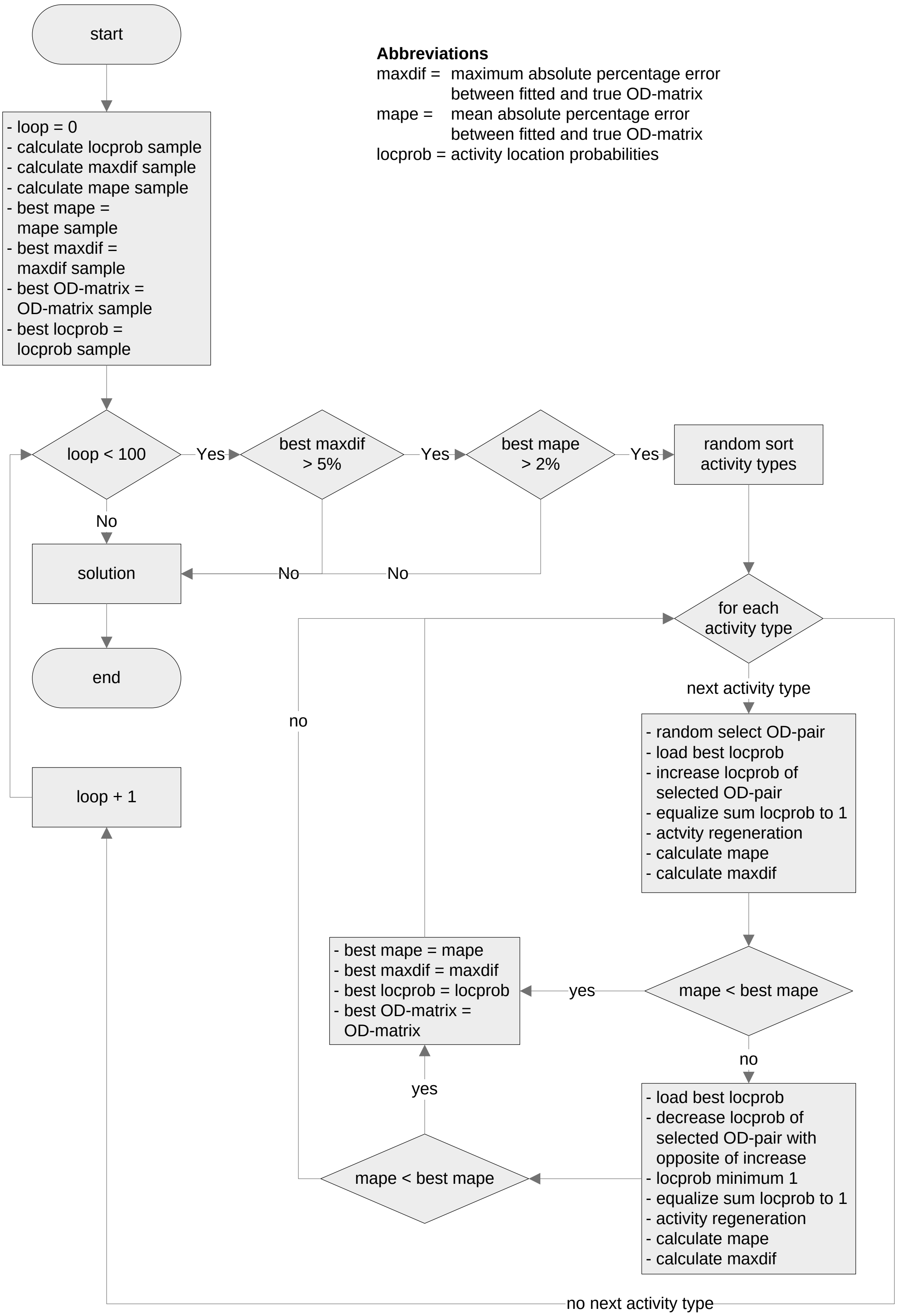

FIGURE 3 Calibration algorithm to adjust activity location probabilities.